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Abstract

The spillover effects of interconnectedness between financial assets is decomposed into both sources of shocks and whether they amplify or dampen volatility conditions in the target market. We use historical decompositions to rearrange information from a VAR which includes sources, direction and signs of effects building on the unsigned forecast error variance decomposition approach of Diebold and Yilmaz (2009). A spillover index based on historical decompositions has simple asymptotic properties, permitting the derivation of analytical standard errors of the index and its components. We apply the methodology to a panel of CDS spreads of sovereigns and financial institutions for the period 2003-2013 and identify how these entities contribute to global systemic risk.

Keywords

Historical decomposition, DY Spillover, Granger Causality, Networks

JEL Classification Numbers

C32, C51, C52, G10

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1 Introduction

Determining the ultimate source of shocks in a complex system of interacting entities is a policy-making nirvana. If the source(s) can be quickly identified with certainty, then policy can be effectively aimed at nudging or alleviating desired or non-desired outcomes. The agenda of understanding the complex interactions in the economy is part of the expanding literature on both economic and financial networks; see for example, Acemoglu et al. (2012), Acemoglu et al. (2015), Pesaran and Yang (2016), and Diebold and Yilmaz (2016).

A concept of interconnectedness, playing a key role in understanding financial networks, is elusive and requires more attention. To estimate network spillovers empirically the method of Diebold and Yilmaz (2009), henceforth DY, for measuring the relative contribution of shocks from alternative sources spilling over to affect others is common in the literature. In this method interconnectedness of the network is defined from a forecast error variance decomposition based on a standard vector auto-regression framework between endogenous variables (see Diebold and Yilmaz (2014)). This approach has gained popularity, with the advantages of being easy to implement and interpret, seemingly nice forecasting properties, simple extensions to varying time horizons and applicable across many different types of application; see for example Yilmaz (2010), Alter and Beyer (2014) and the range of applications presented in Diebold and Yilmaz (2015) and Demirer et al. (2015).

This paper proposes a further development which has the additional advantage of signing the contribution of the sources of volatility into those which augment observed volatility and those which dampen it. We do this by rearranging the information in the standard vector auto-regression to take advantage of the so-called historical decomposition statistics. This decomposition follows from the VARMA form of the residuals in the VAR to attribute the estimated value of an observation to its component shocks. Historical decompositions have been used previously in the macroeconomic VAR literature, such as Dungey and Pagan (2000), Sims (1992) but to our knowledge have not been applied in the way proposed in this paper. The historical decomposition approach to decomposing the sources of shocks and measuring interconnectedness does not require normalization assumptions nor (necessarily) a choice of window length to obtain a time-varying spillover index as in DY method - although this can be accommodated if desired. Assuming asymptotic normality the historical decomposition elements have additive properties so that we can obtain not only the total historical decomposition spillover index from a particular source to a given entity, but also contributions of subsets of historical decompositions, and confidence bands for both.

We provide further insight into the role of shocks that is not evident from unsigned decompositions. The application in this paper is to a set of 107 credit default swap (CDS) spreads for a selection of financial institutions and sovereigns issuing 5 year debt denominated in US dollars over the period 2003-2013. The results track the time-varying contribution of subsectors of the data to overall spreads. For example, we show that the banking sector generally acts to exacerbate spreads during the period of the global financial crisis. Financial institutions are the major recipients of "bad" shocks during the GFC and the European debt crisis. Emerging

and frontier markets are strongly interconnected, while the transmissions from these markets to developed markets are relatively small. Global systemically important banks are the most influential entities using other banks as a critical link in the combined network. We also show that higher order moments of the spillovers contain differing information about the evolution of the spillover index over time.

The remainder of the article is organized as follows. Section 2 introduces a novel interconnectedness measure which takes into account the shocks and whether these shocks amplify or dampen volatility in the target market and provides asymptotic properties of this measure. Section 3 outlines the dataset consisting of daily CDS spreads for sovereign nations and financial institutions. Section 4 discusses the empirical results. Section 5 concludes.

2 Measuring interconnectedness from a historical decomposition

The methodology proposed here provides a new measure of interconnectedness by modifying the Diebold and Yilmaz (2009) approach. By focusing on historical decompositions rather than forecast error variance decompositions we provide the signs of contributory shocks, adding information on whether transmissions augment or dampen the outcomes in the target market.

2.1 Network of sovereigns and financial institutions

Consider N entities indexed by i , N_1 of these entities are financial institutions which lend for projects with uncertain returns as in Diamond (1982), and N_2 are sovereign borrowers, where $N=N_1+N_2$. The financial institutions cannot fund their lending activities from their own balance sheets and establish inter-institutional flows with each other. Following Acemoglu et al. (2015) each financial institution has the opportunity to invest in the real economy with an uncertain return $r_{1,it}$ in period t and/or invest in sovereign bonds with $r_{2,it}$. Incorporating the extension proposed by Dungey et al. (2017a), a sovereign bond return, $r_{2,it}$, is also risky and the values of returns $r_{1,it}$ and $r_{2,it}$ are influenced by an external shock, u_{it} , which is a random variable drawn from a given distribution with mean zero and variance one.¹ The joint probability distribution $p(u_{1t}, \dots, u_{Nt})$ for N entities is assumed to be known. The liabilities between entities creates a network, where the edges are determined by repayments required between pairs of entities.

Definition 1 *Network G is the pair (N, E) , where N is a set of nodes representing entities (banks or sovereigns), and a set of edges E represents contracts between two entities from lender to borrower.*

Definition 2 *A walk P_{j_1, j_k} is a sequence of entities (j_1, \dots, j_k) such that the pairs (j_1, j_2) , $(j_2, j_3), \dots, (j_{k-1}, j_k) \in E$ are edges of the network. The length of the walk P_{j_1, j_k} is given by*

¹Shock u_{it} contains uncertainty about sovereigns and financial institutions and can be seen as an aggregated shock. However, it is trivial to separately analyze disaggregated shocks. Acemoglu et al. (2015) and Glasserman and Young (2015) imply that shocks have a negative impact on returns. In this paper, the shock u_{it} can have either a positive and negative, or indeed insignificant, influence on CDS spreads.

the number of edges k contained in it. The minimal length of the walk P_{j_1, j_k} corresponds to the distance D_{j_1, j_k} .

A distance D_{ij} , introduced in Definition 2, is a measure between two nodes i and j that can be assessed for each entity of a network. The network is characterized by an $N \times N$ adjacency matrix A that contains all information about the network. The adjacency matrix A is a key ingredient defining connectedness of the network. To illustrate this idea suppose that the distance D_{ij} is associated with the length of the continuous function $y = f(x)$ defined for any i and j . Then the distance D_{ij} can be defined by l subintervals each of width Δx . In this case the distance D_{ij} can be approximated by a series of intervals $D_k, k = 1, \dots, l$ as

$$L \approx \sum_{k=1}^l |D_{k-1} - D_k|, \quad (1)$$

which is for large l equivalent to

$$L = \lim_{l \rightarrow \infty} \sum_{k=1}^l |D_{k-1} - D_k|. \quad (2)$$

Now applying the mean value theorem, the length L can be written as

$$L = \int_i^j \sqrt{1 + \left(\frac{dy}{dx}\right)^2} dx. \quad (3)$$

Equation (3) implies that the distance D_{ij} , defining the adjacency matrix A , is fully characterized by the derivative $\left(\frac{dy}{dx}\right)^2$ that should be calculated to obtain the connectedness measure of the network. This derivative can be estimated via forecast error variance decompositions, which is consistent with the DY approach².

We distinguish two types of connections from our historical decomposition approach: amplifying or dampening. A positive weight represents an amplifying connection whereas a negative weight represents a dampening connection.³ Taking into account that CDS spread prices reflect a perceived risk of default, favorable news decreases the value of the CDS spread, while unfavorable news increases the value; thus positive weights A_{ij} identify entities that increase systemic probability of default, while entities associated with negative values A_{ij} reduce the risk of default in the network. This idea can be formally linked to equation (3) implying that the weights assigned to edges of the network can take both positive and negative values. In this instance a generalized length metric GL is defined as

$$GL = \int_i^j \operatorname{sgn} \left(\frac{dy}{dx} \right) \sqrt{1 + \left(\frac{dy}{dx} \right)^2} dx, \quad (4)$$

in which sgn is a signum function.

²An alternative approach, as in Billio et al. (2012) is to define an adjacency matrix A from Granger causality tests, in which case $A_{ij} = 1$ if i and j are connected, or $A_{ij} = 0$ otherwise $\forall i, j$.

³Jorion and Zhang (2007) emphasize the importance of positive and negative transfer effect in the CDS market - they assign positive correlations across CDS spreads as contagion effects, and negative correlations as competition effects.

Definition 3 In a directed weighted network, each node has two degrees. The out-degree $\delta_i^{out} = \sum_{j=1}^N A_{ji}$ is the number of outgoing edges emanating from a node i , and the in-degree $\delta_i^{in} = \sum_{j=1}^N A_{ij}$ is the number of incoming edges to a node. The total degree of the node is defined as $\delta^{tot} = \delta^{in} + \delta^{out} - A_{ii}$.

Once an adjacency matrix, A , is estimated, its degree distribution is the probability distribution of degrees across node, and the overall network connectedness is defined as the mean of the degree distribution (following Diebold and Yilmaz (2014)).⁴ This connectedness measure facilitates understanding of the dampening and amplification mechanisms of systemic risk in more detail. For example, ‘robust-but-fragile’ networks (see Haldane (2009); Acemoglu et al. (2015)) may emerge in the face of small unexpected shocks to the systematic factor that causes losses for many entities. The fragility of a network is characterized by the total size of cumulated small negative shocks which increase network connectedness, and the systemic default probability, which depends only on the absolute value of shocks. We permit elements of the adjacency matrix, A_{ij} , to be negative and consequently allow for dampening: a small negative shock strongly affecting the entity with high systemic risk exposure can be offset by another positive shock.

We use the approach to assess the time-variability of network connectedness, which requires assessing higher moments of the degree distribution. Oh and Patton (2016) highlight the significance of modeling covariation and coskewness in CDS spreads. In this paper the first four central moments of the degree distribution are directly evaluated from an adjacency matrix A . We construct the mean of the degree distribution, estimated ignoring signs of spillovers, which corresponds to the DY aggregate spillover index and conveys similar information. The variance, skewness and kurtosis of signed spillovers may uncover shifts in different phases of a crisis. Such timing differences open an avenue for the construction of early warning measures of contagion and the propagation of systemic risk.

2.2 A weighted directed network of historical decompositions

We propose to measure connectedness elements, A_{ij} , from shares of historical decompositions for various entities due to external shocks. The historical decomposition explains the fraction of variable i ’s variation at time t due to shocks in variable j . Following Diebold and Yilmaz (2014), system wide connectedness at time t is defined as a sum of all pairwise connectedness measures excluding self-loops in a network.

To take into consideration the possibility of common stochastic trend(s) between the I(1) CDS series, a Vector Error Correction Model (VECM) is used:

$$\Delta Y_t = \alpha \beta' Y_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta Y_{t-i} + \varepsilon_t, \quad (5)$$

⁴Alternative connectedness measures such as network diameter $D_{max} = \max_{i,j} D_{ij}$ can be also used in these settings.

where $Y_t = [Y_{1,t}, \dots, Y_{n,t}]'$, $\Delta Y_{t-i} = Y_{t-i} - Y_{t-i-1}$ and α, β, Γ are the parameters of the model.⁵ The rank of the matrix $\Pi = \alpha\beta'$ is estimated by the Johansen test and imposing the triangular restrictions of Phillips (1991). The parameters of model (5) are obtained by applying OLS.

A VECM in (5) can be represented as a VAR(k)

$$Y_t = \sum_{i=1}^k \Phi_i Y_{t-i} + \varepsilon_t, \quad (6)$$

with cross-equation restrictions $\Phi_1 = \alpha\beta' + \Gamma_1 + I_n$, and $\Phi_i = \Gamma_i - \Gamma_{i-1}$, $i = 2, 3, \dots, k$.

The reduced form VAR(k) from equation (6) can be rewritten in terms of disturbances and initial conditions by applying the moving average representation as

$$Y_t = \text{initial values} + \sum_{i=0}^{\infty} S_i \varepsilon_{t-i}, \quad (7)$$

where $S_j = \Phi_1 \Phi_{j-1} + \Phi_2 S_{j-2} + \dots$ for $j = 1, 2, \dots$ with $S_0 = I_N$ and $S_j = 0$ for $j < 0$ and S_j are causal and square-summable. Any individual element $Y_{j,t}$ can be represented by contributions of all variables as

$$Y_{j,t} = \text{initial values} + \sum_{i=0}^{t-1} S_i^{(j)} \varepsilon_{t-i}^{(j)}, \quad (8)$$

which represents the historical decomposition of variable j at time t . Ignoring initial conditions⁶, equation (8) can be rewritten in a matrix form as

$$HD_{t+j} = \sum_{i=0}^{\infty} IRF_i \circ \Upsilon_{t+j-i} = \sum_{i=0}^{j-1} IRF_i \circ \Upsilon_{t+j-i} + \sum_{i=j}^{\infty} IRF_i \circ \Upsilon_{t+j-i}, \quad (9)$$

where \circ is a Hadamard product, $\Upsilon_{t+j-i} = [\varepsilon_{t+j-i}, \dots, \varepsilon_{t+j-i}]$ is the $n \times n$ matrix containing residuals, IRF_i are non-orthogonalized one unit impulse response matrices and HD_t is a historical decomposition matrix at time t . While other definitions of impulse responses including orthogonalized or generalized IRFs of Koop et al. (1996) and Pesaran and Shin (1998) are possible, they do not permit individual components of HD_t to add up to $Y_t, \forall t$. This additive property allows interpretation of the elements of historical decompositions HD_t as shares of CDS spreads, measured in basis points, contributing to the total systemic default probability.

Another important implication of equation (9) is that the historical decomposition HD_t is a function of impulse responses weighted by residuals ε_t , consistent with the view that connectedness is a weighted measure of shocks spreading through the network. Moreover, the historical decomposition HD_t contains two different terms. The far right term represents the expectation of Y_{t+j} given information available at time t , which is the base projection of Y . The first term on the right-hand side shows the difference between the actual series and the base projection due to innovations subsequent to period t . In particular, it shows that the gap between an actual series and its base projection is the sum of the weighted contributions of the innovations to the

⁵ A constant term is suppressed for simplicity.

⁶ Initial values will be ignored in the forthcoming empirical sections following Hualde and Robinson (2010), with the consequence that a first part of the data do not provide empirically analytical decompositions.

individual series. This reveals the dynamic properties of the network as a system that evolves over time by deviating from its long run state. Elements of the historical decomposition matrix $HD_{t,ij}$ lay a foundation of connectedness measures from j to i denoted by $c_{i \leftarrow j}^t$. It is convenient to analyze a connectedness matrix $C^t = [HD_{t,ij}]$ where off-diagonal entries measures pairwise directed connectedness. In general $c_{i \leftarrow j}^t \neq c_{j \leftarrow i}^t$ as in- and out-degrees are not restricted to be identical. This allows us to define net pairwise directional connectedness as $c_{ij}^t = c_{j \leftarrow i}^t - c_{i \leftarrow j}^t$, which is not restricted to be positive. Taking into account that the sum of off-diagonal elements of the j -th row of C^t gives the signed share of the historical decomposition coming from shocks related to other variables, total directional connectedness from others to i is defined as

$$c_{i \leftarrow others}^t = \sum_{j=1, j \neq i}^n HD_{t,ij}, \quad (10)$$

and total directional connectedness from j to others as

$$c_{others \leftarrow j}^t = \sum_{i=1, i \neq j}^n HD_{t,ij}. \quad (11)$$

Furthermore, net total directional connectedness can be calculated for n variables as $c_i^t = c_{others \leftarrow i}^t - c_{i \leftarrow others}^t, \forall t$. To summarize pairwise directional connectedness for the sample T , we define

$$c_{ij} = \frac{1}{T} \sum_{t=1}^T HD_{t,ij} \quad \forall i \neq j, \quad (12)$$

which can be interpreted as a static measure of connectedness⁷ between entities i and j .

The total of the off-diagonal entries in C^t defines the aggregate spillover index measuring total completeness at time t as

$$HDS^t = \frac{1}{n} (e' C^t e - \text{trace}(C^t)). \quad (13)$$

where e is the selection vector of ones.

2.3 Asymptotic properties of a signed spillover index

The main objective now is to provide expressions for the asymptotic standard errors of the signed spillover index. For this purpose suppose γ is a vector of parameters and $\hat{\gamma}$ is an estimator such that

$$\sqrt{T}(\hat{\gamma} - \gamma) \xrightarrow{d} N(0, \Sigma_\gamma), \quad (14)$$

where \xrightarrow{d} is assigned to convergence in distribution and $N(0, \Sigma_\gamma)$ denotes the multivariate normal distribution. Let $F(\gamma) = (F(\gamma_1), \dots, F(\gamma_m))'$ be a differentiable function with values in m -dimensional Euclidean space and $\partial F_i / \partial \gamma' = (\partial F_i / \partial \gamma_j)$ is nonzero at γ for $i = 1, \dots, m$. Then, following Lütkepohl (1990),

$$\sqrt{T}[F(\hat{\gamma}) - F(\gamma)] \xrightarrow{d} N(0, \frac{\partial F}{\partial \gamma'} \Sigma_\gamma \frac{\partial F'}{\partial \gamma}). \quad (15)$$

⁷Static connectedness can be also defined as an expectation of c_{ij}^t over the whole sample.

This general result provides the form of an asymptotic covariance matrix for the signed spillover index derived from the partial derivatives of F and the variance covariance matrix Σ_γ .

Proposition 1 *Suppose*

$$\sqrt{T} \begin{bmatrix} \hat{\eta} - \eta \\ \hat{\sigma} - \sigma \end{bmatrix} \xrightarrow{d} N \left(0, \begin{bmatrix} \Sigma_\eta & 0 \\ 0 & \Sigma_\sigma \end{bmatrix} \right).$$

Then

$$\sqrt{T} \text{vec}(\widehat{HD_i} - HD_i) \xrightarrow{d} N(0, \Psi_i \Sigma_\eta \Psi_i'), i = 1, 2, \dots,$$

where

$$\Psi_i = \partial \text{vec}(HD_i) / \partial \eta' = \sum_{m=0}^{i-1} R_{i-1-m} G_m,$$

in which $G_i = \sum_{m=0}^{i-1} J(\Phi')^{i-1-m} \otimes S_m$, $\eta = \text{vec}(\Phi_1, \dots, \Phi_k)$, $\sigma = \text{vech}(\Sigma_\varepsilon)$, $J = [I_n \ 0 \dots 0]$, R_i is the diagonal n^2 -variate matrix containing residuals $\text{vec}(\varepsilon_i, \dots, \varepsilon_i)$ on the main diagonal and

$$\Phi = \begin{bmatrix} \Phi_1 & \Phi_2 & \dots & \Phi_{k-1} & \Phi_k \\ I_n & 0 & \dots & 0 & 0 \\ 0 & I_n & & 0 & 0 \\ \vdots & & \ddots & \vdots & \vdots \\ 0 & 0 & \dots & I_n & 0 \end{bmatrix}.$$

Here vec denotes the column stacking operator and vech is the corresponding operator that stacks only the elements on and below the diagonal and \otimes is the Kronecker product.

Proof: Appendix

Proposition 1 shows that an asymptotic variance-covariance matrix of the historical decomposition HD_i is characterized by residuals, parameters of the model and one unit impulse responses. Matrix Σ_η can be estimated as $\Sigma_\eta = (ZZ'/T)^{-1} \otimes \Sigma_\varepsilon$, $Z_t = [Y_t, \dots, Y_{t-k+1}]'$, $Z = (Z_0, \dots, Z_{T-1})$ for VAR models and as

$$\Sigma_\eta^{co} = T \begin{bmatrix} Y_{-1} Y_{-1}' & Y_{-1} \Delta X' \\ \Delta X Y_{-1}' & \Delta X \Delta X' \end{bmatrix}^{-1} \otimes \Sigma_\varepsilon^{co}$$

for VECMs. In this case $Y_{-1} = [Y_0, \dots, Y_{T-1}]$ and $\Delta X_{t-1} = [\Delta Y_{t-1}, \dots, \Delta Y_{t-k+1}]$ and Σ_ε^{co} is a variance-covariance matrix from VECM (see e.g. Lütkepohl (2005)). In the forthcoming empirical study CDS spreads are I(1) series and for this reason the VAR with cross equation restrictions, defined in equation (6), is chosen as a benchmark model. The asymptotic variances from Proposition 1 do not go to zero, but converge to the respective long run values with the sample size. An implicit convenient assumption of equation (6) is that Y_t has zero mean. The results of Proposition 1 remain valid if a nonzero mean term, a polynomial or a seasonal component is removed prior to estimating the VAR parameters. Equivalently, polynomial or seasonal trends can be included in the model (6) and estimated jointly with other coefficients without affecting Proposition 1. This follows from the fact that the asymptotic variances in Proposition 1 only depend on parameters Φ_i and a variance-covariance matrix Σ_η .

While Proposition 1 has been stated for individual historical decomposition coefficient matrices, one can extend these results for the case where the elements of \widehat{HD}_i and \widehat{HD}_j , $i \neq j$, are not independent asymptotically. If elements of two or more HD_i matrices are included in the null hypothesis the joint distribution of all the matrices can be estimated using Proposition 1. In particular, the covariance matrix of the joint asymptotic distribution of $\text{vec}(\widehat{HD}_i, \widehat{HD}_j)$ is

$$\frac{\partial \text{vec}(HD_i, HD_j)}{\partial \eta'} \Sigma_\eta \frac{\partial \text{vec}(HD_i, HD_j)'}{\partial \eta},$$

in which

$$\frac{\partial \text{vec}(HD_i, HD_j)}{\partial \eta'} = \begin{bmatrix} \partial \text{vec}(HD_i) / \partial \eta' \\ \partial \text{vec}(HD_j) / \partial \eta' \end{bmatrix}.$$

Now the results of Proposition 1 can be used to obtain the asymptotic distribution of the interconnectedness index based on historical decompositions.

Proposition 2 *Suppose $Q_i = \text{diag}(\Psi_i \Sigma_\eta \Psi_i' / T)$ is a vector of parameter variances and HDS^i is a spillover index defined from a historical decomposition in (13). Then*

$$\sqrt{T}(\widehat{HDS^i} - HDS^i) \xrightarrow{d} N(0, (e' W_i e - \text{trace}(W_i)) / n), i = 1, 2, \dots, \quad (16)$$

where $W_i = \text{unvec}(Q_i)$ and operator unvec is the inverse of the vec operator such that $W_i = \text{unvec}(\text{vec}(W_i))$.

Proof: Appendix

Proposition 2 permits the estimation of the standard error of HDS^i as a square root of variance defined in (16). An important assumption for Proposition 2 is that a historical decomposition is a unique transformation of data. Moreover, non-diagonal elements of a historical decomposition matrix HD_j are orthogonal by construction, which allows us to obtain the confidence bounds for the historical decomposition spillover index by taking average across the non-diagonal elements of W_i . A similar approach can not be applied to the DY spillover index as appropriate normalization restrictions that ensure forecast error variance components sum up to 1 are required. These restrictions make the derivation of the asymptotic distributions of variance decomposition components difficult. Thus, the asymptotic distribution of the DY index can not be obtained in the usual way for setting up confidence intervals.

3 Data

Modeling the interconnections between financial institutions is hampered by data availability. On the one hand, many of the theoretical frameworks are expressed in terms of inter-entity flows. However, these data are exceedingly difficult to obtain, particularly outside the commercially available data sets; a good example is the UK interbank network in Giratis et al. (2016), who use data available to the Bank of England. On the other hand, there is a strand of literature that takes advantage of market-based data as proxies to develop an understanding of the interconnectedness of networks, as in, for example, Billio et al. (2012) and Merton et al. (2013). Recent

work by van de Leur et al. (2017) finds that interconnectedness networks based on market data produce valuable information that is not offered by alternative approaches. The work in this paper draws on the market-based data tradition in this literature.

Table 1: Sovereigns included in CDS sample data. D-Developed, E-Emerging, F-Frontier markets according to the MSCI classification.

Europe	Asia	Latin America
Bulgaria (F)	Australia (D)	Argentina (F)
Czech Republic (E)	China (E)	Brazil (E)
Denmark (D)	Indonesia (E)	Chile (E)
Norway (D)	Japan (D)	Colombia (E)
Poland (E)	Malaysia (E)	Mexico (E)
Sweden (D)	Philippines (E)	Panama (F)
Russia (E)	South Korea (E)	Peru (E)
Turkey (E)	Thailand (E)	Venezuela (F)
Ukraine (F)	Vietnam (F)	
Africa	Euro Zone	North America
Israel (D)	Belgium (D)	USA (D)
Morocco (F)	Finland (D)	
South Africa (E)	France (D)	
Qatar (F)	Germany (D)	
	Ireland (D)	
	Italy (D)	
	Netherlands (D)	
	Portugal (D)	
	Spain (D)	

The dataset consists of daily five-year CDS spreads for 40 sovereign nations and 67 financial institutions as listed in Tables 1 and 2. Five-year CDS contracts are the most commonly issued and traded asset in this class and are the most liquid (Duca and Peltonen (2013), Pan and Singleton (2008), Kalbaskaa and Gatkowskib (2012)). The data are sourced from Markit and run for the period January 1, 2003 to November 21, 2013.⁸ The sample has 107 nodes and potentially 11342 ($= 67!/65!$) links.

The sample contains three different phases; Phase 1 represents the non-crisis period from January 1, 2003, to September 14, 2008. This is typical of dating conventions used in literature to separate the pre-crisis and crisis periods; see the review of dates extant in the literature in Dungey et al. (2015). Phase 2 represents the period from September 15, 2008, to March 31, 2010, consistent with the global financial crisis (GFC) and period following. The end of March 2010 represents the period prior to which the Greek debt crisis became critical in April 2010. Phase 3, from April 1, 2010, to November 21, 2013, represents the period of the Greek and European sovereign debt crises. Summary statistics, reported in Table 3, show an increase in spread means for

⁸Our data finished in November 2013 for the initial drafts of this paper. On updating the dataset we found that there were significant changes in later data due to the Dodd-Frank Act and the implementation of the so-called Volker rule which affected new-issuance of US dollar denominated CDS for many of the institutions in our sample.

most groups of institutions and sovereigns, reflecting the perceived increase in risk during this turbulent period in international debt markets. Skewness in Phases 2 and 3 are both lower than in phase 1, except Asia and Europe (phase 2), which implies less asymmetry. Moreover, kurtosis is much higher before the GFC for most of the entities. Some of these results might reflect actions taken by the authorities that were more aggressive in the US than in Europe (see Borio and Zabai (2016)).

CDS spreads were found to be non-stationary, $I(1)$, with a maximum of one unit root according to KPSS and ADF tests.

Table 2: Financial institutions grouped by broad type. SIB - Global Systemically Important Banks.

Banks	Financials	Insurance
Aust & New Zld Bkg	ACOM CO LTD	ACE Ltd
Amern Express Co	John Deere Cap Corp	Aegon N.V.
Barclays Bk plc (SIB)	MBIA Inc.	American Intl Gp Inc
BNP Paribas (SIB)	Natl Rural Utils Coop	Allstate Corp
Cap One Finl Corp	Aiful Corp	Aon Corp
Citigroup Inc (SIB)	ORIX Corp	Assicurazioni Generali
Ctrywde Home Lns	Gen Elec Cap Corp	CHUBB CORP
Kookmin Bk	Goldman Sachs Gp Inc	CNA Finl Corp
Commerzbank AG (SIB)	Morgan Stanley	Legal & Gen Gp PLC
Deutsche Bk AG (SIB)	SEARS ROEBUCK	MBIA Ins Corp
Hana Bank	Toyota Mtr Cr Corp	MetLife Inc
HSBC Bk plc (SIB)	Swire Pac Ltd	Munich Re
ING Bk N V (SIB)		Old Mut plc
Korea Dev Bk		Safeco Corp
Merrill Lynch & Co		Mitsui Sumitomo Ins
Mizuho Corporate Bk (SIB)		Sompo Japan Ins Inc
Macquarie Bk Ltd		HARTFORD FIN INC
Natl Aust Bk Ltd		Loews Corp
Oversea Chinese Bkg		
Rabobank Nederland		
Royal Bk of Scotland (SIB)		
Resona Bk Ltd		
Societe Generale (SIB)		
Std Chartered Bk (SIB)		
Sumitomo Mitsui Bkg (SIB)		
UBS AG (SIB)		
Wells Fargo & Co (SIB)		
Westpac Bkg Corp		
Investment	Real Estate	
Daiwa Secs Gp	EOP Oper Ltd Pship	
Bombardier	Hammerson PLC	
Nomura Secs	Hongkong Ld Co	
	Mitsubishi Estate Co	
	Simon Ppty Gp L P	
	Simon Ppty Gp Inc	

Table 3: Summary statistics are reported for all sovereign CDS spread data used in this paper. The selected phases are respectively consistent with the pre-GFC, the GFC and the European debt crisis.

	Obs.	Mean	Std dev	Skewness	Kurtosis
Phase 1	01/01/2003 - 14/09/2008				
Banks	1488	0.4253	0.6634	6.2252	73.1315
Financials	1488	0.7426	1.4386	9.2843	131.738
Insurance	1488	0.5413	1.1174	10.551	146.240
Investment	1488	1.0126	1.6023	3.5076	19.9933
Real Estate	1488	0.5737	0.5135	2.5807	11.3350
Latin America	1488	3.3274	5.0302	4.3823	24.8403
Asia	1488	1.0935	1.3470	1.4863	4.1704
Euro Zone	1488	0.0698	0.0759	2.8669	11.6775
Europe	1488	0.9062	1.5211	2.8717	13.9841
Africa	1488	0.8038	0.7205	2.5980	11.9358
North America	1488	0.0262	0.0311	2.9249	11.0294
Phase 2	15/09/2008 - 31/03/2010				
Banks	403	1.6490	1.2574	2.1977	8.4938
Financials	403	12.719	32.619	6.6554	58.383
Insurance	403	3.6890	5.1029	2.4613	9.2081
Investment	403	1.9650	1.1711	1.0721	2.8133
Real Estate	403	2.6080	2.4492	1.4525	4.1223
Latin America	403	6.3541	8.8135	2.2891	7.7371
Asia	403	2.0159	1.5864	1.7696	7.0876
Euro Zone	403	0.8250	0.5597	1.5966	6.8034
Europe	403	3.4588	6.4693	3.8884	20.298
Africa	403	1.9245	0.9750	1.3394	4.5551
North America	404	0.4169	0.1834	1.1935	3.9374
Phase 3	01/04/2010 - 21/10/2013				
Banks	951	1.3971	0.6334	1.6584	6.8687
Financials	951	6.3933	10.211	2.0464	5.9045
Insurance	951	1.8314	2.1538	3.7857	20.033
Investment	951	1.4738	1.0772	0.5886	2.2274
Real Estate	951	1.1053	0.4586	0.6091	2.8172
Latin America	951	3.7769	5.6733	3.1106	14.840
Asia	951	1.3284	0.7275	1.6687	6.1909
Euro Zone	951	2.5872	2.5487	1.9267	7.1373
Europe	951	1.6592	1.9220	2.2460	7.9880
Africa	951	1.4990	0.5059	0.5376	2.5000
North America	951	0.3067	0.0801	-0.2616	2.3762

4 Empirical results

4.1 Static connectedness

Figure 1 shows the average historical decomposition of the shocks contributing to observed CDS spreads for each of the sovereign nations in the sample. That is, the vertical axis indicates the recipient issuing country, and the horizontal axis gives the contributing shocks measured as the sample average of those shocks across the historical decomposition. Lighter colours indicate a positive transmission - that is the shock increases the CDS spread in the recipient market. Darker colours indicate a negative transmission - the shock decreases the CDS spread in the recipient market. The table is primarily shaded approximately at average of zero recipient/transmission shocks - on average the effects are largely cancelled out over the sample.

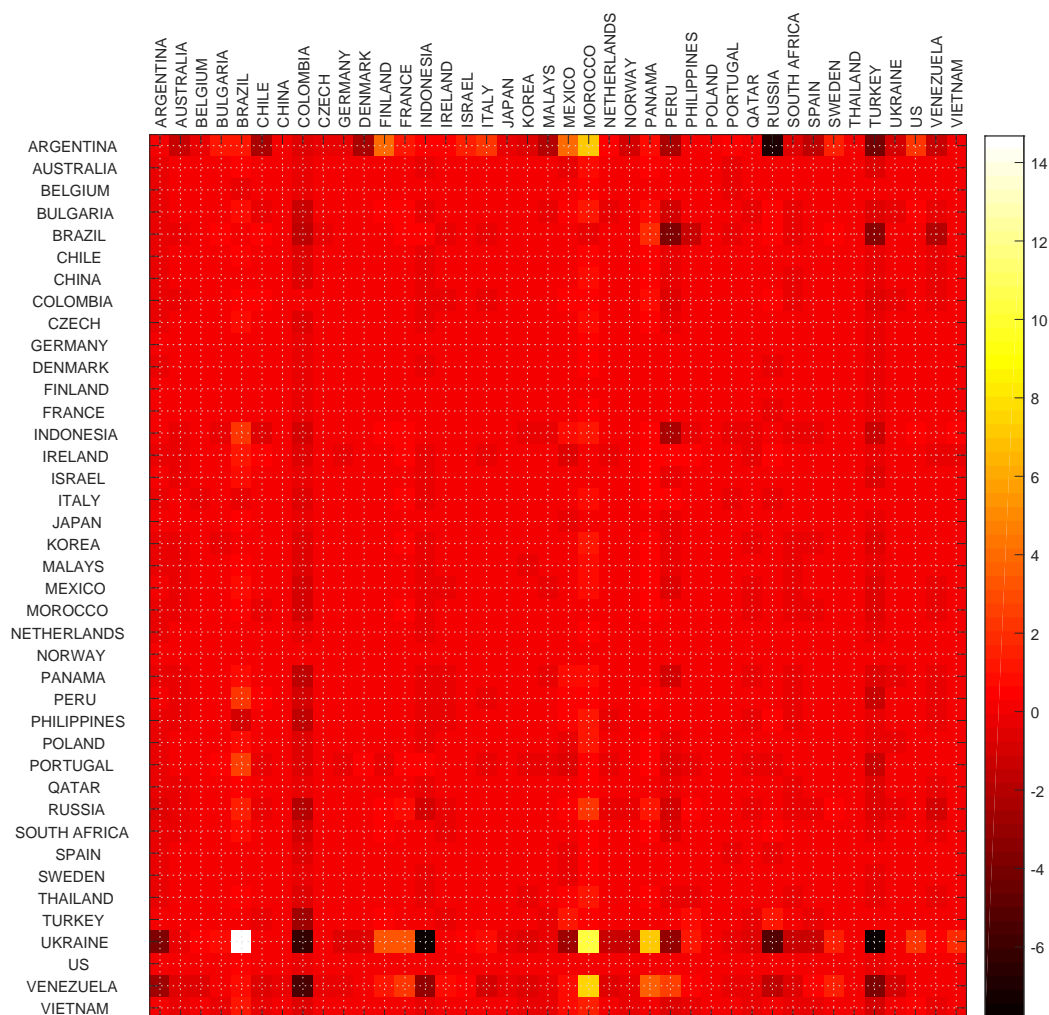


Figure 1: Heat map for sovereigns. Effects from columns to rows represent averages of historical decompositions over the whole sample. Dark colors show negative contributions to CDS spreads, bright colors - positive contributions.

It is critical to differentiate negative in-shocks from positive out-shocks in the figure - across the rows gives the sources and signs of in-shocks to the target listed in a particular row; down the columns gives the effect of out-shocks sourced from the country listed for that particular column to each of the potential recipients listed down the column.

Reading across rows there are a few countries which show some variety in their sources of shocks. Consider, the row labelled Argentina which exhibits both amplifying and dampening shocks sourced from its partners. Shocks from Peru and Columbia are strongly negative, decreasing the CDS spreads for Argentina. However, shocks from Venezuela, Morocco and Turkey on average increase the CDS premium for Argentina. In a network framework each of these directionally represents an in-shocks from the contributing markets but they are signed as to whether they amplify or dampen the effects of those shocks on Argentina. Other interesting examples of markets which display skew in their sources of shocks (across the rows) are Ireland, Portugal, Spain, Italy, Ukraine and Venezuela, that is they include members of the so-called GIIPS group, experienced civil unrest or were located in South America.

Figure 2 shows the same heat map for the financial institutions network. Reading across rows it is apparent that AIF, AIG, MBI, MBC and to some extent SHC receive a diverse set of shocks.⁹ Looking at the columns for the sources of shocks, we can see that AIG, MBI and MBC are not distinctly different to other companies. These institutions are subject to diverse shocks, but do not emit shocks which strongly impact in one way or the other.

Thus insurers are performing the role of absorbing and smoothing shocks coming from other institutions and emitting shocks with little signed effect on other financial institutions. From this point of view these insurers are acting to stabilise the financial system, rather than potentially disrupt it. This result supports arguments that the role of insurers in the system is distinct to that of credit creating institutions; see Biggs and Richardson (2014).

There are also two distinctly different vertical lines in Figure 2; from BOM (Bombardier Capital Incorporated) and SWI, a Hong Kong based conglomerate. Both of these firms are heavily invested in the transport and asset financing sector. The result that transport finance is important in spreading shocks is interestingly paralleled by the recent finding of Pesaran and Yang (2016) that the transport and warehousing sector of the US economy is routinely the most important sector of the US economic network.

To illustrate how the distribution of shock effects changes over the sample period, Figure 3 presents the histograms of the sizes of the shocks in each of the three phases of the sample: pre-GFC, GFC and European debt crisis. The top panel shows the distribution of the shocks in the financial companies component of the network and the lower panel the distribution for the sovereigns. In the pre-crisis period, the mode of 0 is pronounced and tails are relatively small for both panels. During the GFC and European debt crises we see that the distribution moves to the right - that is there are more positive (amplifying) shocks present than pre-crisis. The distribution is more leptokurtic, implying a greater proportion of larger signed shocks. These

⁹MBI and MBC are the insurance and financial arms of the same company (MBIA), and represent the largest bond insurer in the market. The Aiful Corporation (AIF) is a Japanese financial services provider.

changing higher-order moments of our shocks are consistent with the findings in Fry et al. (2010) that contagion and crisis are evident in higher-order moments of returns and volatilities.

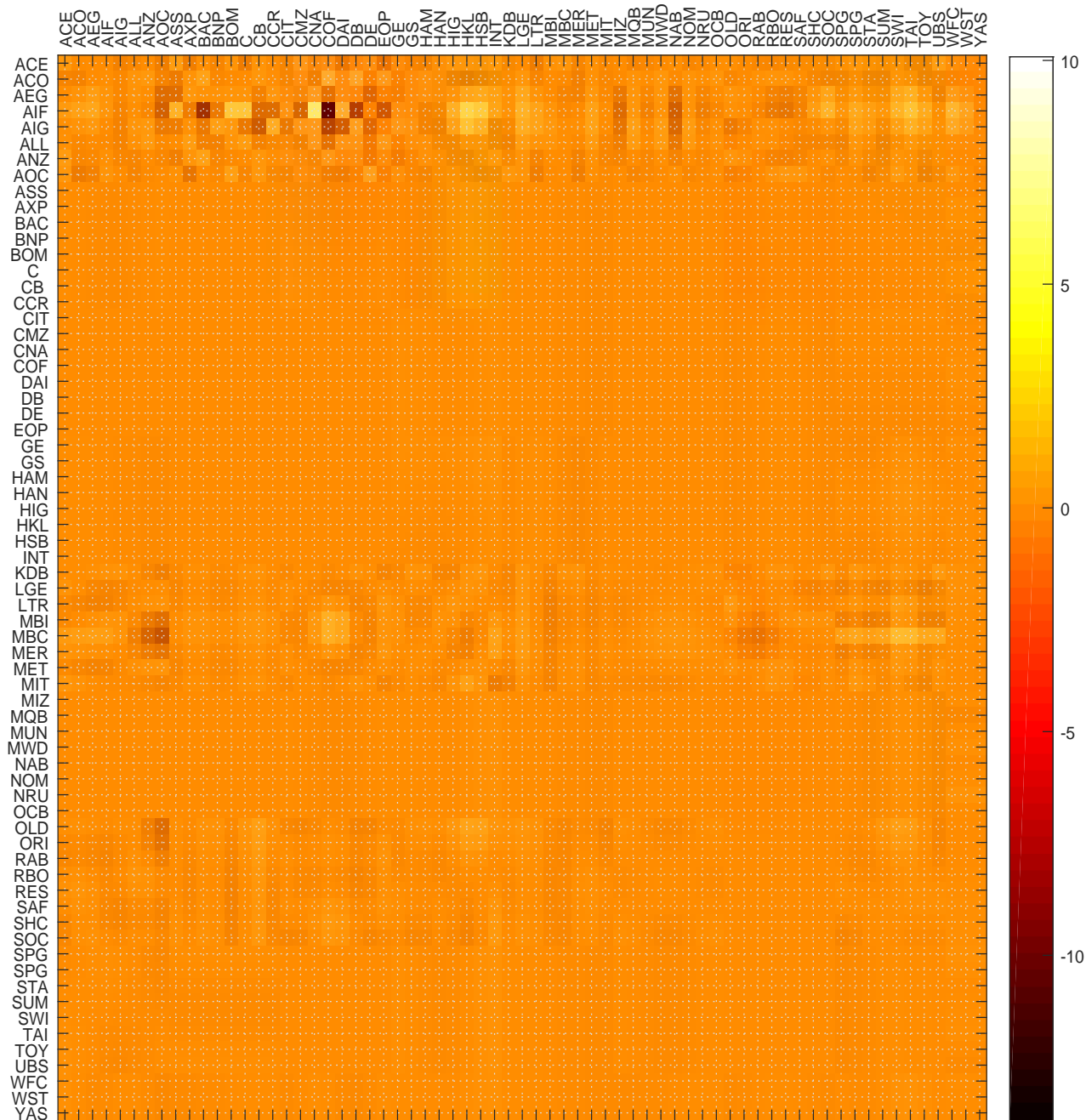


Figure 2: Heat map for financial companies. Effects from columns to rows represent averages of historical decompositions over the whole sample. Dark colors show negative contributions to CDS spreads, bright colors - positive contributions.

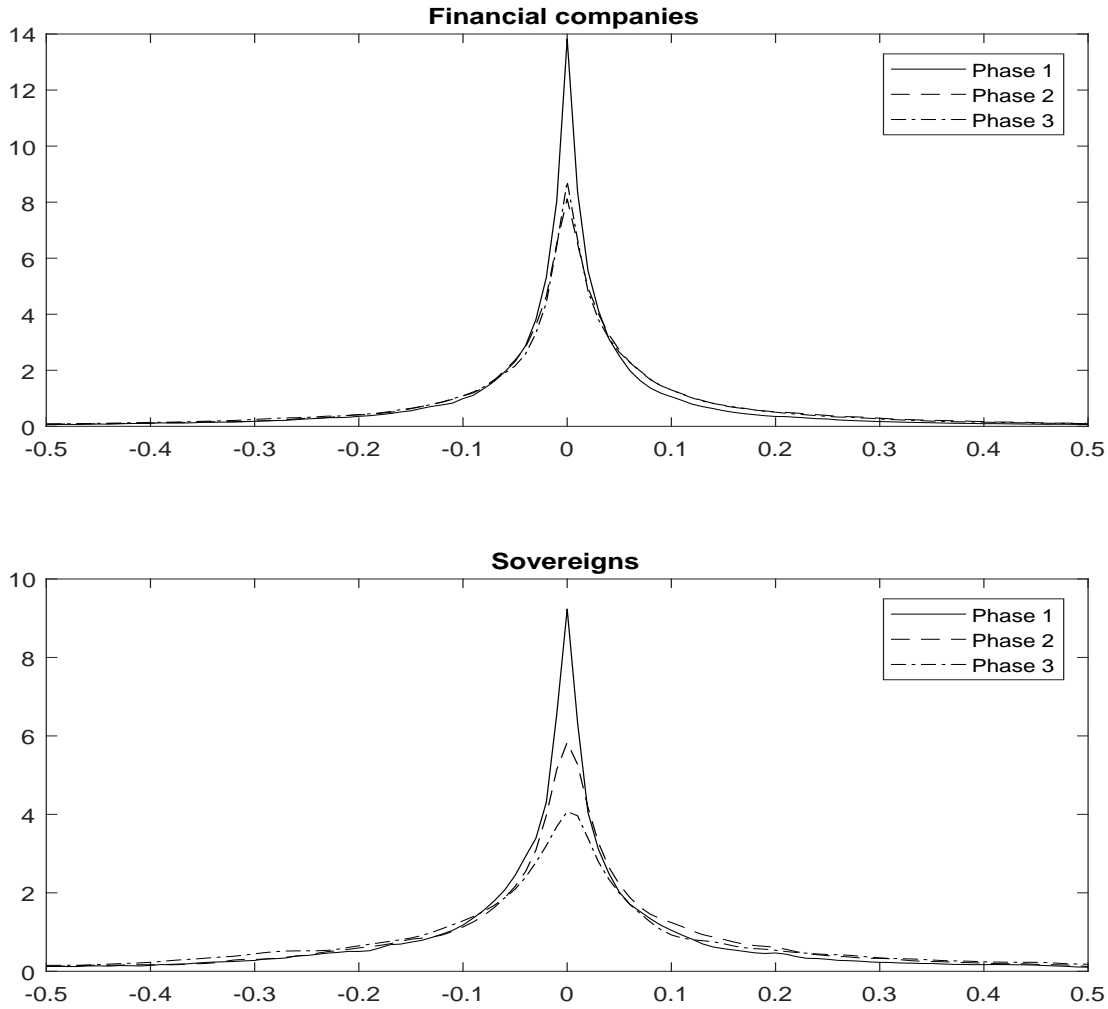


Figure 3: Densities for 3 phases (pre-GFC, GFC and European debt crisis). Dates of these phases are presented in Table 3.

4.2 Dynamic connectedness

As well as the average effects discussed in the previous section we also compile spillover indices based on the DY methodology (with 10 day ahead forecast period) and using the proposed historical decomposition method. These are shown in Figure 4. The nature of the construction of these indices means that the scales are quite different - the HD method has a direct interpretation of the average size of the spillovers to CDS spreads from all sources in the system, and it can be seen that this is typically quite small, and often insignificant in the early part of the analysis via the 68% error confidence bands. The DY index has larger (always positive) values due to normalization between 0 and 1 discussed in the previous sections. The DY spillover index increases dramatically in mid-2007, probably associated with the events of Bear-Stearns and hedge funds in the middle of that year. The HD model picks up at that point, but picks up

much more substantially at a date closer to the stress associated with Lehman Bros collapse and the subsequent problems in the remainder of the system. Interestingly, the DY spillover index does not fall dramatically with the introduction of TARP or the NBER dating of the ending of the US recession as often used elsewhere in the literature (see Dungey et al. (2005) for a review) but remains elevated. The DH index, however shows some reduction in the effect of the spillovers on CDS spreads post the GFC, but a resurgence of positive effects around the period of uncertainty surrounding the future of Greece in late 2009 - early 2010 and the re-emergence of uncertainty again around European debt markets in 2011 and 2012.

Figure 5 presents the HDS indices for the financial institutions and the sovereigns separately extracted from the combined network. It is immediately apparent that the spillover effects from the two sources have dramatically different time paths. Prior to the GFC from mid-2008, financial institutions were in fact behaving in a way which reduced the average CDS spread. Only when the GFC became well-established did the contribution of financial institutions peak, and even then, the greatest contributions were observed in 2009, rather than around the time of the collapse of Lehman Bros. The error bands shown in the diagram widen substantially around early 2010 when the Greek crisis, subsequent IMF programs and European debt problems unfolded. During the period from 2009 the contribution to spillovers in the CDS markets from sovereigns has been unerringly positive, and on average more than 4 times greater than during the GFC. This pattern differs from Bostanci and Yilmaz (2015) who found that connectedness of the global sovereign market by the end of 2013 returned back to the same level as it was before the GFC.

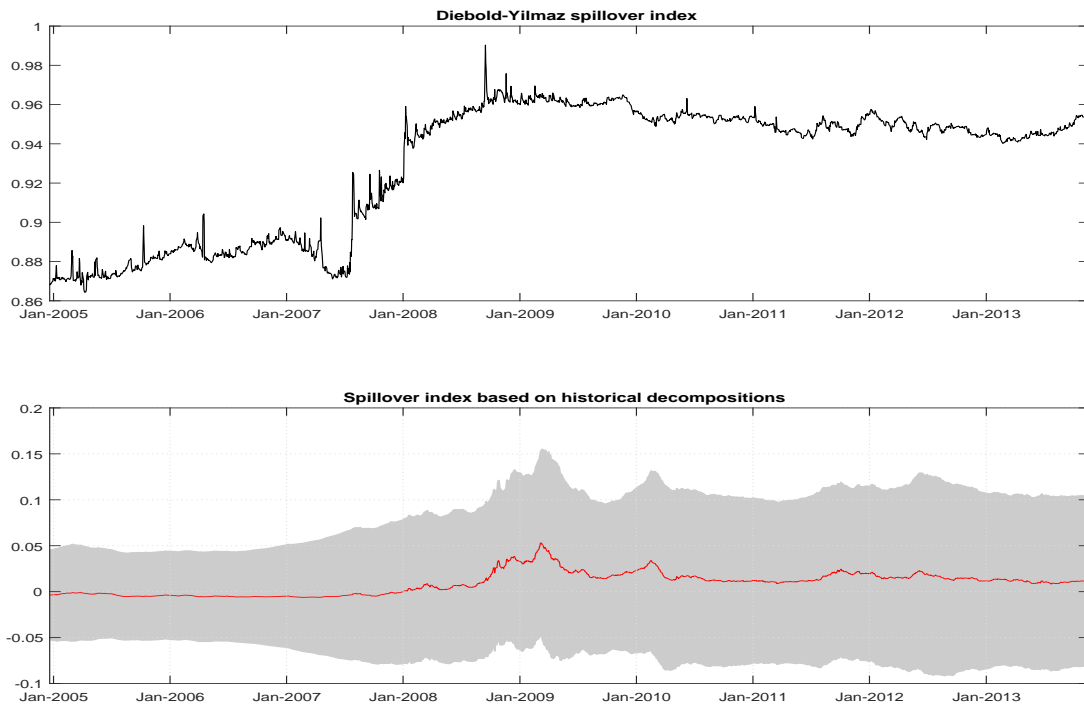


Figure 4: DY and HDS indices estimated from equation (13) for 107 spreads. Shaded areas represent 68% confidence intervals.

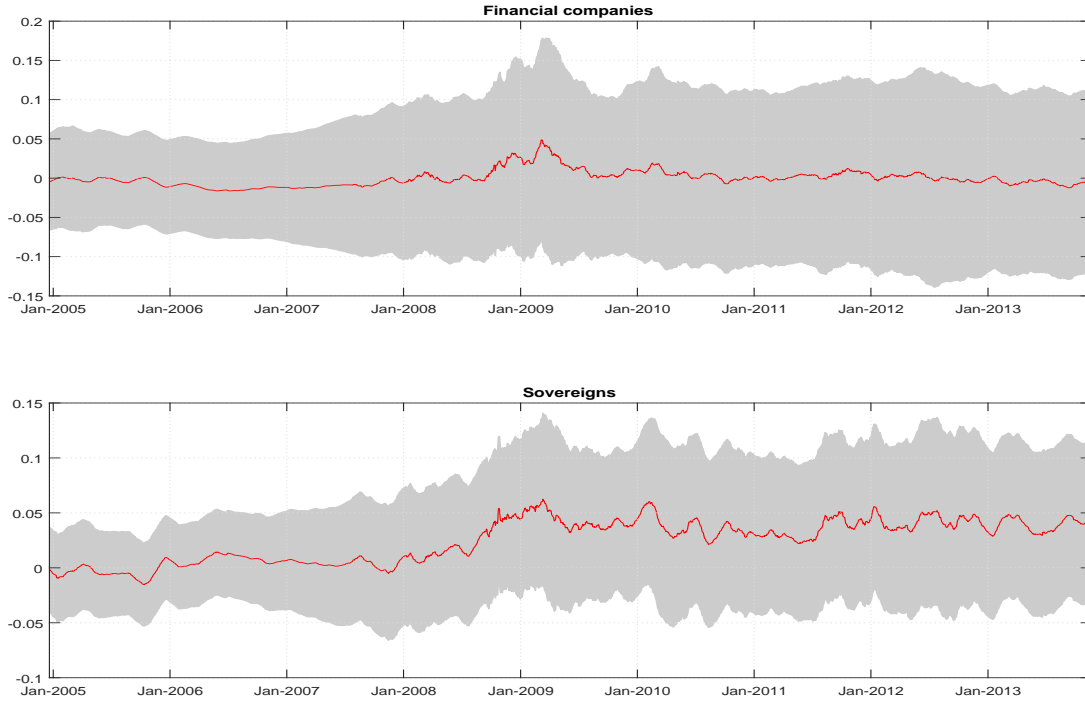


Figure 5: HDS indices for financial institutions and Sovereigns. Shaded areas represent 68% confidence intervals.

4.3 Contributions by source type

As the contributions of each of the sources of shock are additive in our approach we can compile sub-series which illustrate the contribution of particular groupings on the spread. For each of the types of financial institutions Figure 6 shows their HDS spillover indices as both recipients of shocks (left hand panels) and as spreaders of shocks (right hand panels). It is useful to point out that the scales for each sub-figure differ, sometimes substantially.¹⁰

The main result from Figure 6 is that the largest spreaders of shocks is the banks (top right hand panel). Other spreaders have a substantially smaller impact on the rest of the system. As recipients, however, the banks do not receive a great deal of impact from others (top left hand panel). With the exception of the financial institutions category all other types spread shocks more than they receive them. When receiving shocks, each of the left hand panels of Figure 6 shows that the shocks received amplified volatility (that is were positive effects) during the 2008-2009 crisis, although the confidence bands do not indicate significance in all cases. However, in the spreading of shocks, during the crisis of 2008-2009 and through to 2010 it is very apparent that each category of institution had a different role. Banks were contributing to dampening shocks in the system prior to the GFC, but rapidly became amplifiers and have largely remained that way since. However, insurers had a dampening effect during 2009-2011, the period prior to the largest

¹⁰Using the same scales is analytically intractable.

disruptions in European markets. That is, the insurers were at this time receiving amplifying shocks and distributing dampening ones. The other particularly interesting spreader category is real industry (bottom right panel) where industry shocks were dampening shocks prior to the GFC. During the build up to the GFC and its initial stages industry shocks were amplifying, but this was reversed during late 2008, consistent with the breaking of linkages between the real economy and financial sector noted in Dungey et al. (2017b) due to the introduction of TARP and rescue of AIG.

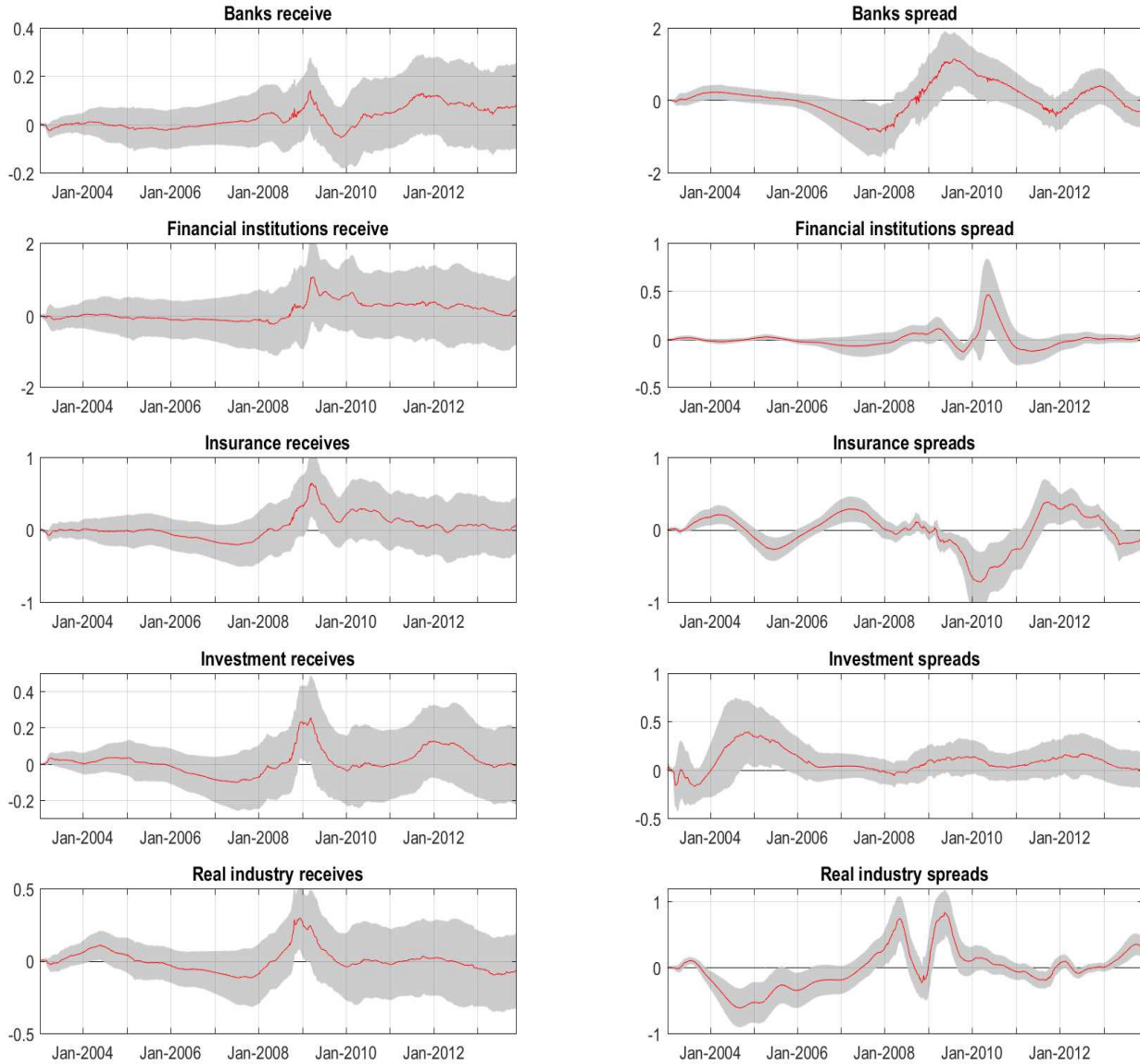


Figure 6: Interconnectedness between different groups of financial institutions with 95% confidence intervals estimated from equation (16).

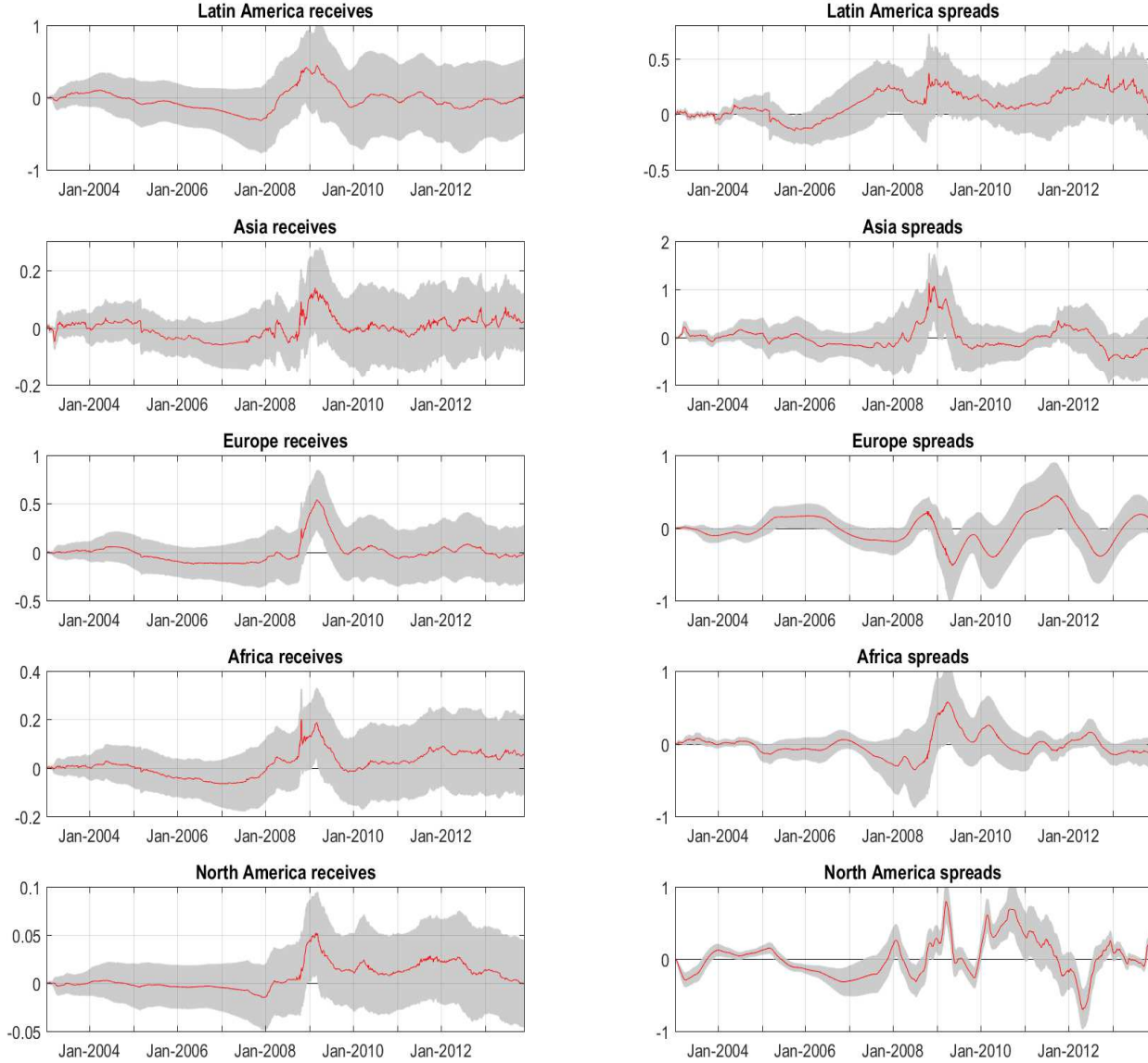


Figure 7: Interconnectedness between different groups of financial institutions with 95% confidence intervals estimated from equation (16). Eurozone is not presented as the respective HDS index is not informative and close to zero.

Figure 7 represents the geographical influences of receiving and spreading of shocks. Each panel represents the average effect of a shock from the spreading region to the recipient region (this scales the shocks for comparison, given that there are, for example, many more issuers in Europe than North America for example). Europe is the recipient of the largest impact of shocks, although these were experienced during the problems of the period of late 2008 during the post-Lehman Bros turmoil, and during the remainder of the sample the effects from the rest of the world markets were quite subdued¹¹. The largest analytical difference is that prior to 2009 the majority of the received shocks dampened European CDS spreads, whilst after 2009

¹¹Note that 80% of financing comes from banks in Europe and only 20% in the US, see Gambacorta et al. (2014).

they largely amplified them (although in neither case are these effects statistically significant). The spreading of shocks from Europe shows a different picture, during the period prior to mid-2010 Europe largely spread effects which subdued CDS spreads elsewhere, that is they calmed perceptions of risk elsewhere. However, during the period of 2011 particularly they contributed (insignificantly) to amplifying shocks.

The region which spreads on average the largest contributions is Asia, where during 2008-2009 Asia contributed to the amplification of spreads in CDS markets substantially, and significantly. For the majority of the rest of the period Asia mainly contributed dampening effects on other markets - although these were almost uniformly insignificant. In contrast, Asia was not recipient of a large dampening or amplifying effects from anywhere in the rest of markets - tying with analysis that sees Asian markets as largely end-point nodes, or in a separated market, from other markets.

Latin American receives relatively larger (insignificant) effects from the rest of the world, which as with Europe, were dampening prior to the 2008-09 crisis, and with largest amplifying impact during the crisis period and then a reduced effect thereafter. The profile is similar for Africa.

North America, which was at the centre of the GFC, and often regarded as the generating market in the literature, reveals that as a recipient it sees very small effects from other regions on its own CDS spreads. There is a slight period at the height of the turmoil around Lehman Bros where the impact of transmission from other markets was statistically amplifying North American CDS premia, and evidence that thereafter that the average (insignificant) effect is positive. In contrast, the average effects spread from North America are statistically significant and relatively large. Prior to 2008, the transmissions originating in the US had been dampening CDS spreads since mid-2005. The first evidence of amplifying shocks occurs in late 2007 and early 2008 and from the third quarter of 2008 until approximately the period associated with the end of the NBER dated recession in mid 2009 the effects of US originated shocks clearly amplify CDS premia elsewhere. A brief intermission of neutral to dampening shocks precedes a further period of amplification in 2010-2011 associated with the debt crisis, before the US transmissions become a stabilizing force from mid-2011 to mid-2012. This particular example clearly demonstrates how much influence the US, as a central world market has on the rest of the world, and how clearly the transmission channels can change in whether they amplify or dampen the transmission of shocks. Clearly it is not sufficient to know which markets are on average amplifying or dampening spreaders to each recipient, one needs also to keep track of these effects over time.

4.4 Developed vs emerging markets

We segment the results on spillovers by stage of market development using the IMF classification of developed, emerging and frontier markets, see Table 1. The contribution of shocks sourced from markets at different stages of development to the recipient markets are illustrated in Figure 8.

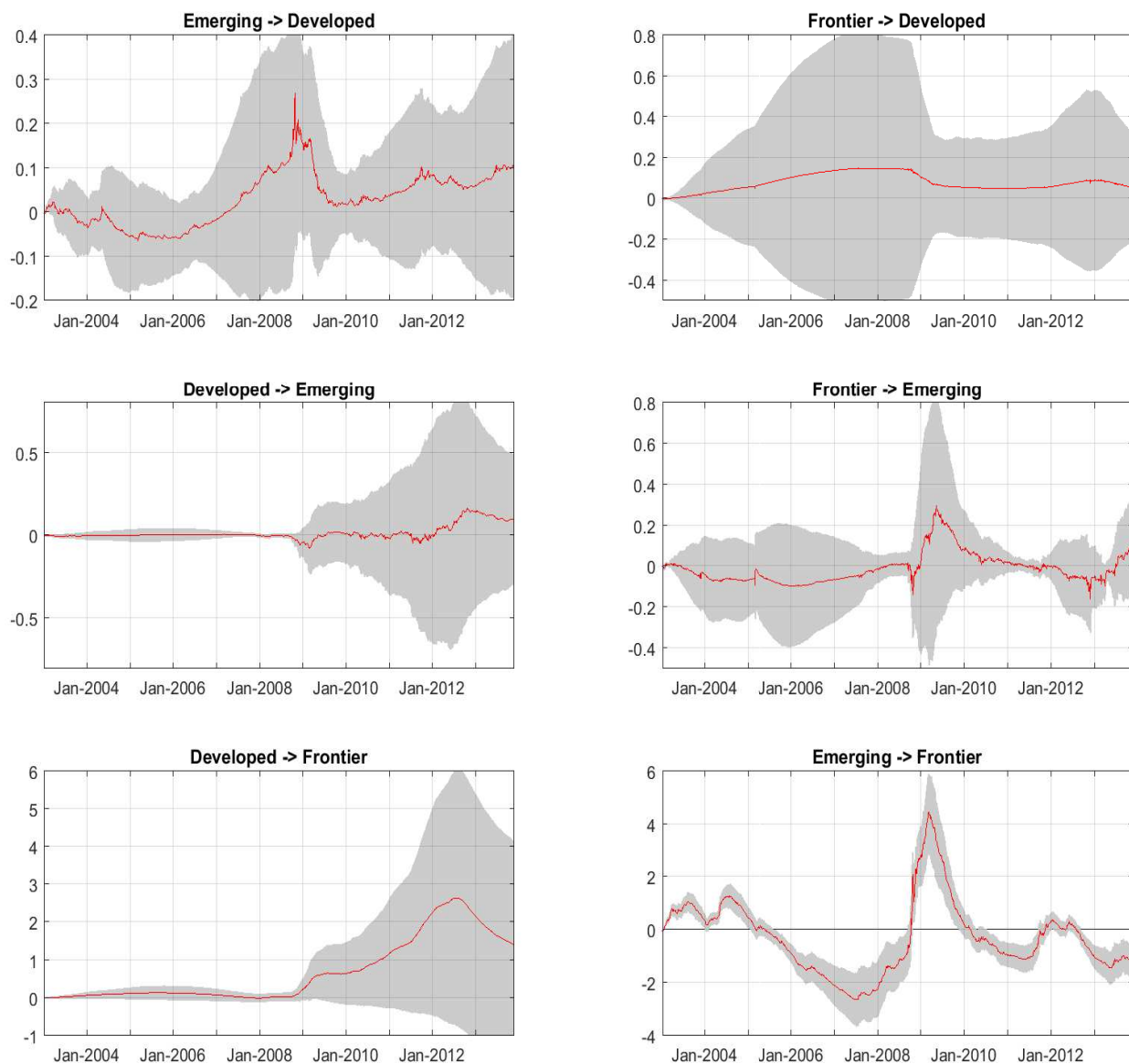


Figure 8: HDS indices for developed and emerging markets with 95% confidence intervals estimated from equation (16).

The transmissions to developed markets from emerging and frontier markets (the top panel of Figure 8) are relatively small. Emerging markets were a net source of dampening for developed markets prior to the GFC, and have remained a source of increased premia since, although this peaked during late 2008. The effects from frontier markets on developed markets are more consistently positive, although less volatile. Emerging markets have received little increase in CDS premia as a result of shocks from developed markets¹² (in contrast to the centre and

¹²This finding is consistent with Chen et al. (2016) who found that emerging markets became economically

periphery arguments of Kaminsky and Reinhart (2003), while shocks in frontier markets reduced CDS premia in emerging markets prior to 2009 for a period until 2012. In the other direction, however, frontier markets received substantial premium amplification from developed markets after 2009, and particularly post the 2012 problems in European sovereign debt markets. Frontier markets received more volatile effects from emerging markets - prior to 2009, emerging market shocks were dampening frontier market spreads, possibly attracting investors to these markets - but the risks were rapidly reassessed in late 2008, early 2009, and frontier markets suffered a

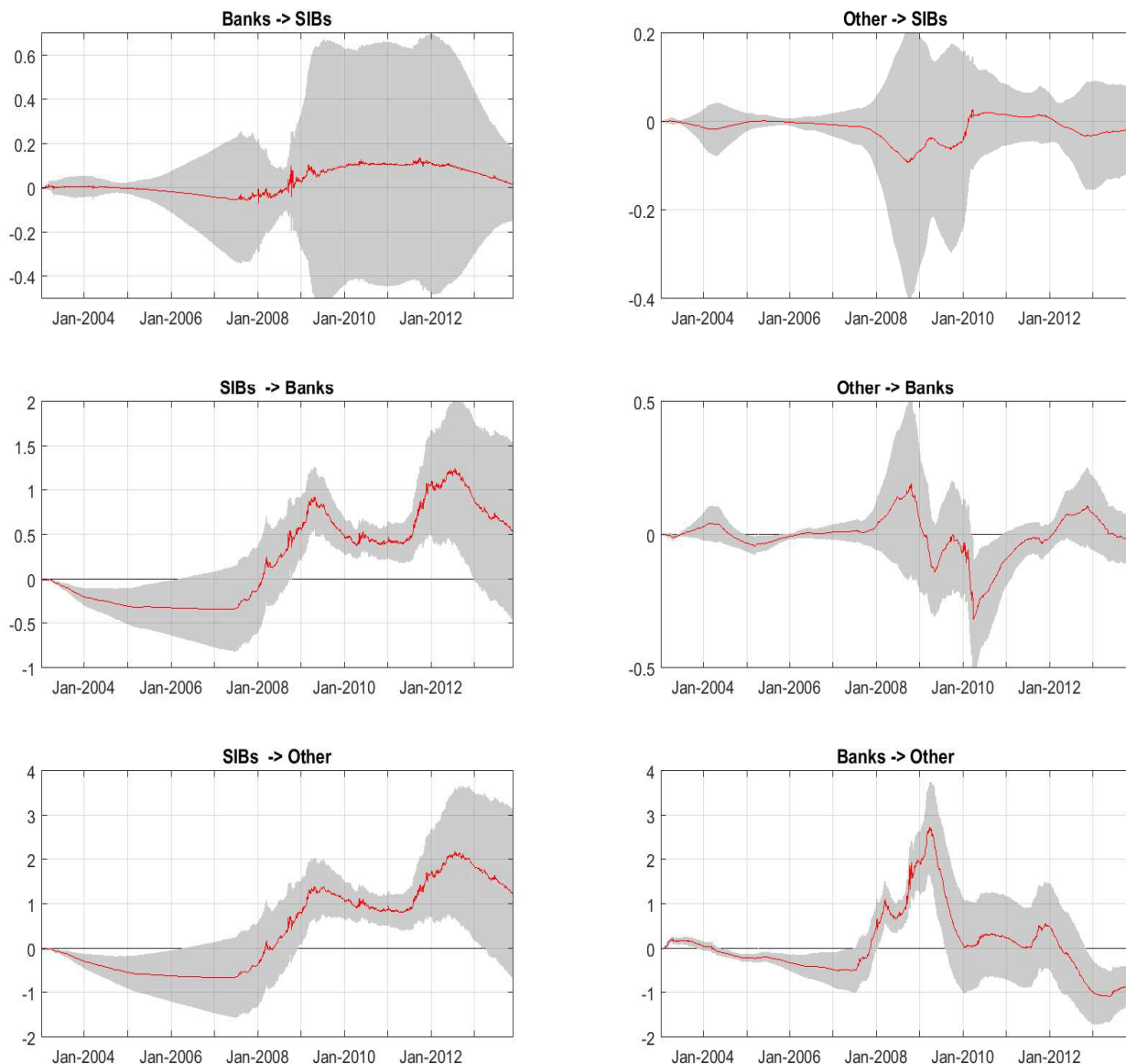


Figure 9: Systemically important banks vs other banks and the rest of the world. A detailed classification is presented in Table 2.

more resilient after the GFC.

4.5 Global systemically important banks

Figure 9 provides spillover indices between banks which have been designated as globally systemically important (SIBs), other banks and other types of financial institutions. It is immediately clear that the largest effects are apparent in shocks spreading from SIBs to Banks and other types of institutions. The SIBs are clearly an import source of shock amplification, consistent with the literature which supports regulating banks for systemic risk reasons. However, the influence of shock amplification from SIBs to other entities is not more significant than amplification from other banks to other parts of the network. That is, while SIBs are important it is not clear that to non-banks there is a huge distinction between SIBs and non-SIB institutions. While SIBs were generally a source of amplifying shocks from 2008 onwards, the non-bank sector transmissions were dampening the transmissions to the banks. This may be an indication of the successful application of policy which aimed to prevent credit restrictions from reducing economic activity in the GFC period, but without a clear counterfactual it is difficult to be conclusive. The clearest message from the SIB and non-SIB distinction is that SIBs have a larger and more certain amplifying effect on other banks than other banks do on SIBs.

4.6 Index distribution and moments

While the mean bilateral spillover, defined in (13), provides a summary of network activity, it may obscure a great deal of relevant information, particularly if the degree distribution is asymmetric and has significant kurtosis. This information is particularly valuable during the crisis when banks with greater upper tail dependence have higher CDS spreads (see e.g. Meine et al. (2016)). A more complete summary of spillover activity must take account not only of the location but also of the shape of the spillover density. For a given moment t , one may approximate the empirical distribution of pairwise spillover effects via kernel density estimation (see e.g. Greenwood-Nimmo et al. (2017)).

Consider an $h \times 1$ vector of grids $z = (z_1, \dots, z_h)'$, which covers the range of pairwise spillovers in matrix C^t . The density of pairwise spillovers is estimated from

$$\hat{g}_t(z_k) = \frac{1}{b_t} \left(\frac{1}{n(n-1)} \right) \sum_{i,j=1; i \neq j}^n K\left(\frac{z_k - c_{ij}^t}{b_t}\right), \quad k = 1, \dots, h, \quad (17)$$

where K is a kernel and b_t is a bandwidth at time t . To ensure that $\hat{g}_t(z_k)$ integrates to unity over the selected range of grid points, the following standard normalization is employed as

$$\hat{f}_t(z_k) = \frac{\hat{g}_t(z_k)}{RIE(\hat{\mathbf{g}}_t)}, \quad (18)$$

where $RIE(\hat{\mathbf{g}}_t)$ denotes a numerical Riemann sum of $\hat{\mathbf{g}}_t = (\hat{g}_t(z_1), \dots, \hat{g}_t(z_h))'$. Following Silverman (1986), a Gaussian kernel with the rule-of-thumb bandwidth $b_t = 1.06\hat{\tau}_t(n(n-1))^{-0.2}$, is considered as a benchmark, where τ_t is the cross-sectional standard deviation of c_{ij}^t . However, given that the spillover density exhibits departure from normality when working with CDS data,

right and left skew might be pronounced.¹³

In this section we combine the information on pairwise connectedness, C^t , with the Granger-causality approach to detecting network direction and significance of Billio et al. (2012) and Merton et al. (2013). This approach reduces the dimensionality of the problem, by removing all non-Granger caused links. Billio et al. (2012) propose that Granger-causality links have an advantage over direct correlation in providing a lead-lag dimension. Significant Granger causality from entity i to entity s indicates that Y_i has at least one significant lag predicting the value of Y_s , indicating that the perceived risk of entity i defaulting predicts the perceived risk of default of entity s . The edges of the network constructed from these Granger causality links represent predictors of each node's perceived risk of default. Moreover, Granger causality established edges map clearly to the existing empirical frameworks for measuring and testing contagion during financial crises via the formation and breaking of linkages (the overarching framework for this is provided in Dungey et al. (2005)).

Once a VAR form of the model is estimated from (6), Granger causality between CDS spreads Y_i and Y_s can be assessed using the Wald test

$$WT = [e \cdot \hat{\eta}]' [e(\hat{V} \otimes (Y'Y)^{-1})e']^{-1} [e \cdot \hat{\eta}], \quad (19)$$

in which Y is the matrix of independent variables represented by CDS spreads, $\hat{\eta}$ denotes the row vectorized coefficients of VAR discussed earlier, $\hat{V} = T^{-1} \sum_{t=1}^T \hat{\varepsilon}_t \hat{\varepsilon}_t'$ and e is the $k \times 2(2k+1)$ selection matrix

$$e = \begin{bmatrix} 0 & 1 & 0 & 0 & \dots & 0 & 0 & \dots & 0 & 0 \\ 0 & 0 & 0 & 1 & \dots & 0 & 0 & \dots & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & 0 & \dots & 1 & 0 & \dots & 0 & 0 \end{bmatrix}.$$

Each row of e selects one of the coefficients to set to zero under the non-causal hypothesis $Y_i \rightarrow Y_s$.

The results of the Wald test indicating Granger causality are recorded as binary entries in matrix \tilde{A} as

$$\tilde{A} = [\tilde{a}_{is}],$$

where

$$\tilde{a}_{is} = \begin{cases} 0, & \text{if } Y_i \text{ does not Granger cause } Y_s \\ 1, & \text{if } Y_i \text{ Granger causes } Y_s \end{cases}.$$

Matrix \tilde{A} is used to construct the directional edges between sovereigns and banks.

Given the estimates of the matrix \tilde{A} and the spillover matrix C , the structure of the weighted matrix can be characterized as

$$\tilde{\tilde{A}} = \tilde{A} \circ C,$$

where \circ is the Hadamard product. The elements of the adjacency matrix $\tilde{\tilde{A}}$ now capture the connectedness between entities conditional on the significant causal linkages between them. The

¹³An original DY spillover index often has a right skew and is bi-modal in some cases - requiring a careful robustness check including alternative kernels and bandwidths.

network defined by the adjacency matrix $\tilde{\tilde{A}}$ shows the predictors of the risk of default subject to a shock captured by the matrix C . Using the entries of the matrix $\tilde{\tilde{A}}$, system-wide completeness is measured as

$$\tilde{C} = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^n \tilde{\tilde{a}}_{ij}}{\sum_{\substack{i,j=1 \\ i \neq j}}^n c_{ij}}. \quad (20)$$

The index distribution conditional on the Granger caused linkages between entities is obtained by applying equations (17) and (18) to the non-diagonal entries of the matrix $\tilde{\tilde{A}}$, $\forall t$.

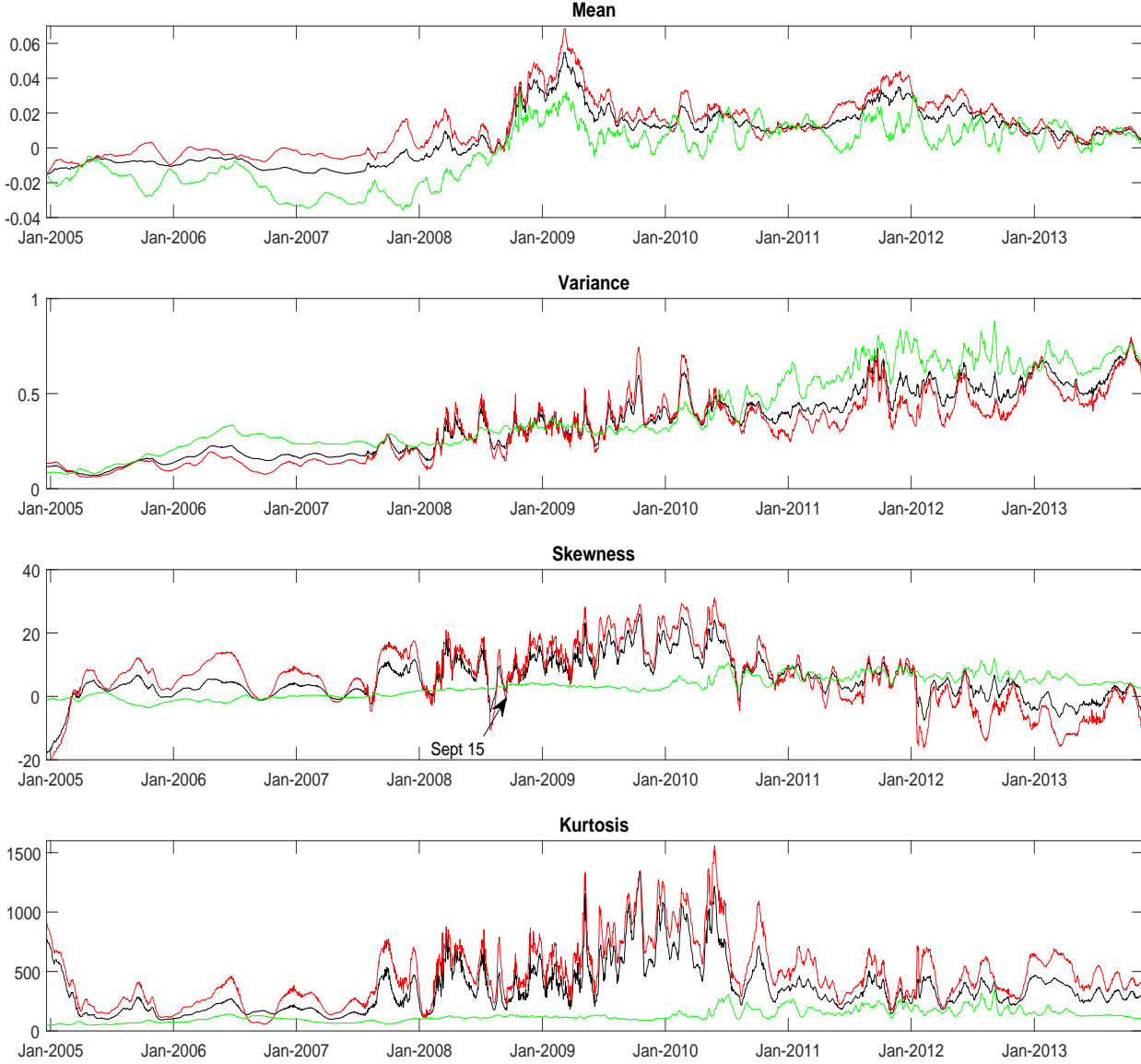


Figure 10: Moments of the spillover density obtained from equations (17) and (18). Black line - all 107, red - financial institutions, green - sovereigns.

The first four moments of the HD spillover index estimates conditional on the Granger caused linkages for all 107 nodes are shown in Figure 10, with the moments for the financial companies and sovereigns indices given separately as the red and green lines respectively. Three things are immediately apparent. First, both skewness and kurtosis of the combined and financial institution networks are positive and co-move during the GFC, which implies significant default risk premia in the financial industry. An interesting pattern in the skewness of these networks is observed on the first day of the GFC (15th of September 2008) when the third moment jumped up by more than 5 basis points. This finding is consistent with Fry et al. (2010) who argue that higher moments are informative in predicting contagion. Second, the spillover variance for all three networks increases across the sample. Moreover, there is a distinctly observable shift from pre-2008 to post-2008 in the level and volatility of each of the indices. Third, while before and during the GFC volatility of the combined network is mainly driven by financial institutions - after the European debt crisis of 2010 the variance of the combined network emanates from both financial institutions and sovereigns. Overall, the sovereigns can be distinguished from the financial institutions in that the increase in variance, skewness and kurtosis comes later in the sample, closer to the problems associated with the Greek and subsequent European sovereign debt crisis.

To summarize the evolution of the whole degree distribution for each time t we construct a sequence of $t = 1, \dots, T$ spillover densities. The pre-crisis period is considered as a benchmark characterized by a density f_{nc} , which is compared with f_{cr} , a density during a crisis. Using the following common divergence criteria, an evolution of the spillover density from a non-crisis to a crisis phase can be assessed as

$$DH(\hat{f}_{cr}, f_{nc}) = \sup_z |\hat{f}_{cr} - f_{nc}| / \sup_z f_{nc}(z), \quad (21)$$

$$DM(\hat{f}_{cr}, f_{nc}) = \int |\hat{f}_{cr}(z)dz - f_{nc}(z)|dz, \quad (22)$$

where \hat{f}_{cr} is the estimated density during the crisis, DH is the Hilbert norm and DM is the distribution mass difference. Each of these quantities is non-negative and takes the value zero if $\hat{f}_{cr} = f_{nc}$. Moreover, $DM \in [0, 2]$, with $DM = 2$ when \hat{f}_{cr} and f_{nc} do not overlap at all over the selected range of grid points.

Using the same spillover densities for the combined network as in Figure 10, we estimate DH and DM quantities for each day t . A non-crisis density f_{nc} is obtained from the historical decomposition spillovers in December 2004. As follows from Figure 11 both DH and DM measures show similar patterns, namely between 2005 and 2007 the difference between the crisis and non-crisis spillover distributions increases and achieves its peak in July 2011. This peak concurs with the beginning of the second economic adjustment programme when Euro area leaders agreed to extend Greek (as well as Irish and Portuguese) loan repayment periods from 7 years to a minimum of 15 years and to cut interest rates to 3.5%. After July 2011 the divergence stays at the same level a sign of a deep crisis in the financial and sovereign CDS markets, confirming the results of Oh and Patton (2016) that the joint probability of distress (a measure of systemic risk) is substantially higher after 2011 than in the pre-crisis period. This finding is

also consistent with the pattern of increasing variance from Figure 10, which allows to consider volatility in the CDS market as the main source of systemic risk. Overall, the analysis of the spillover density across a range of moments permits a deeper understanding of the changing interconnectedness of the global CDS market.

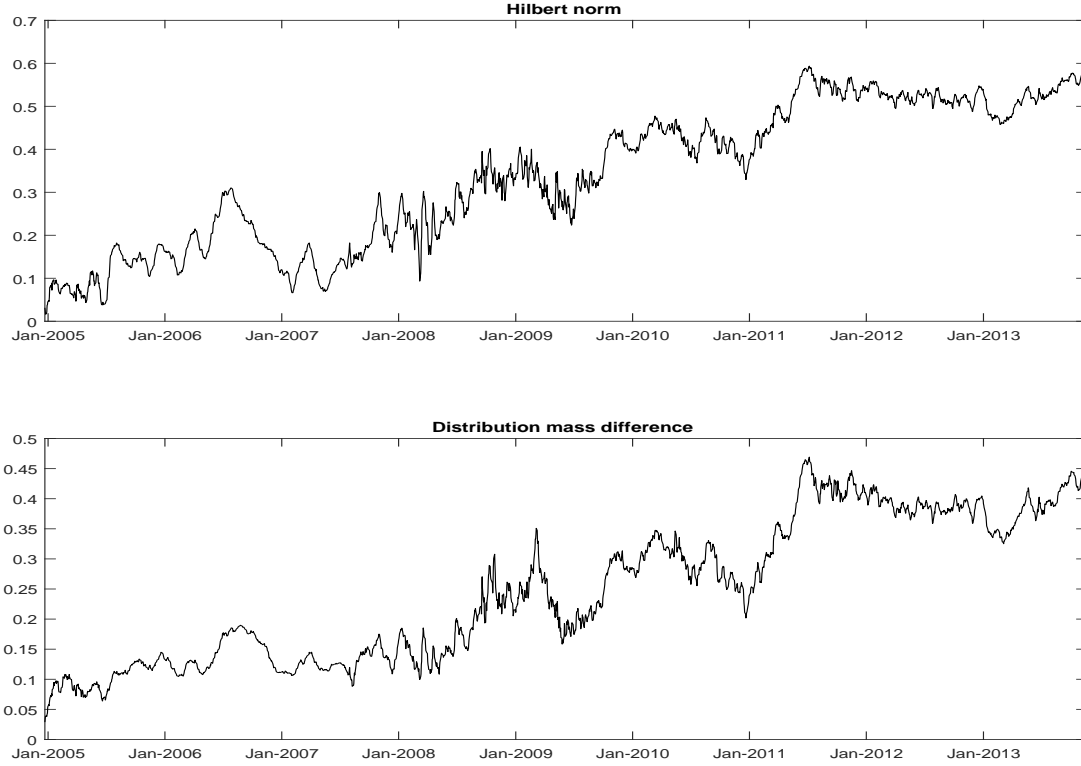


Figure 11: Hilbert norm and Distribution mass difference estimated from equations (21) and (22) respectively for all entities.

5 Conclusion

This paper has shown how an alternative decomposition of the information available in a VAR representation of the strength of network linkages between markets can provide information on sources, direction and whether links amplify or dampen the transmission of shocks across a network. We show how the work relates to the popular (unsigned) Diebold and Yilmaz spillover index, and the extra information which can be obtained by knowing not only the source, direction and relative size of shocks, but also the sign (amplifying or dampening) of their impact. We emphasise that this is a different finding from direction. The direction of a shock indicates the flow of a causal event in one node to the other node. The contribution of signing indicates whether that transmission has a positive or negative impact on the volatility of the target node. This is important for policymakers as not all transmissions necessarily increase volatility, and it may be advantageous during periods of stress to be able to identify and target channels which

exacerbate conditions whilst allowing those which calm them to remain. An example of where these mechanisms are debated in the literature concerns the role of short-sales restrictions.

The proposed interconnectedness measure based on historical decompositions is easy to implement since it does not require a rolling window estimation or any normalization scheme (although these can be imposed if desired). The distribution of our index is asymptotically normal. The orthogonality of elements of historical decompositions permits us to obtain analytical standard errors of the proposed index.

Our empirical findings confirm that both sovereigns and financial institutions significantly contribute to systemic risks of the global CDS market. During the GFC both sovereigns and financial institutions induced high connectedness associated with positive variations in CDS spreads, while after the European debt crisis high spreads were also present for sovereign issuers. Banks are found to be the largest spreaders of shocks, while financial institutions mainly receive systemic risk from others. Developed and emerging countries spread a significant amount of risk which was absorbed by frontier markets. Systemically important global banks used connections with other banks as a critical link in the combined network.

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Appendix A: Asymptotic distribution for the spillover index based on historical decompositions

The following result from Lütkepohl (1990) is used to prove propositions 1 and 2:

(i) Let γ be a vector of parameters and $\hat{\gamma}$ be its estimate. Then

$$\sqrt{T}(\hat{\gamma} - \gamma) \xrightarrow{d} N(0, \Sigma_\gamma), \quad (23)$$

where T is the sample size. Let $F(\gamma) = (F(\gamma_1), \dots, F(\gamma_m))'$ be a vector-valued continuously differentiable function with $\partial F_i / \partial \gamma_j' = (\partial F_i / \partial \gamma_j) \neq 0$ at γ . Then

$$\sqrt{T}[F(\hat{\gamma}) - F(\gamma)] \xrightarrow{d} N(0, \frac{\partial F}{\partial \gamma'} \Sigma_\gamma \frac{\partial F'}{\partial \gamma}). \quad (24)$$

The partial derivative of the historical decompositions HD_i are computed as

$$\begin{aligned} \Psi_i &= \frac{\partial \text{vec}(HD_i)}{\partial \eta'} = \frac{\partial \text{vec}(\sum_{m=0}^{i-1} \Upsilon_{i-m-1} \circ IRF_m)}{\partial \eta'} \\ &= \sum_{m=0}^{i-1} \frac{\partial \text{vec}(\Upsilon_{i-m-1} \circ IRF_m)}{\partial \eta'} \\ &= \sum_{m=0}^{i-1} \text{DIAG}(\Upsilon_{i-m-1}) \frac{\partial \text{vec}(IRF_m)}{\partial \eta'} \end{aligned} \quad (25)$$

$$= \sum_{m=0}^{i-1} \text{DIAG}(\Upsilon_{i-m-1}) G_m, \quad (26)$$

where $\text{DIAG}(\Upsilon_{i-m-1})$ denotes the diagonal matrix displaying the elements of $\text{vec}(\Upsilon_{i-m-1})$ along its diagonal. A derivation of G_m is presented by Lütkepohl (1990). To obtain equations (25) and (26) the following results from Magnus and Neudecker (1985) are used:

$$\frac{\partial \text{vec}(\Upsilon \circ IRF)}{\partial \eta'} = \text{DIAG}(IRF) \frac{\partial \text{vec}(\Upsilon)}{\partial \eta'} + \text{DIAG}(\Upsilon) \frac{\partial \text{vec}(IRF)}{\partial \eta'}. \quad (27)$$

The first term of equation (27) vanishes asymptotically as Υ goes to zero due to $E(\varepsilon_t) = 0$. This proves Proposition 1.

For proving Proposition 2 notice that elements of a historical decomposition matrix HD_i are orthogonal by construction and for this reason the elements of this matrix are independent normal random variables. Consequently equation (13) can be used to obtain an asymptotic covariance matrix of HDS^i . In particular, for $i = 1, 2, \dots$, standard errors are computed as

$$\text{diag}(\Psi_i \Sigma_\eta \Psi_i' / T)^{1/2},$$

which proves Proposition 2.